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Health Outcomes in Poor Countries and Policy Options

Empirical Findings from Demographic and Health Surveys

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Abstract

Empirical studies on health at a disaggregate level—by socioeconomic group or geographic location—can provide useful information for designing poverty-focused interventions. Using Demographic and Health Survey (DHS) data, Wang investigates the determinants of health outcomes in low-income countries both at the national level, and for rural and urban areas separately. DHS data from more than 60 low-income countries between 1990 and 1999 reveal two interesting observations. First is the negative association between the level and inequality in child mortality. Second is the significant gap in child mortality between urban and rural areas, with the rural population having a much slower reduction in mortality compared with the urban population. Given that the poor are mainly concentrated in rural areas, the evidence suggests that health interventions implemented in the past decade may not have been as effective as intended in reaching the poor.

The empirical findings in this study consolidate results from earlier studies and add new evidence. Wang finds that at the national level access to electricity, vaccination in the first year of life, and public health expenditure can significantly reduce child mortality. The electricity effect is shown to be independent of income. In urban areas only access to electricity has a significant health impact, while in rural areas increasing vaccination coverage is important for mortality reduction.

This paper—a product of the Environment Department—is part of a larger effort in the department to better understand health-environment linkages. Copies of the paper are available free from the World Bank, 1818 H Street NW, Washington, DC 20433. Please contact Limin Wang, room MC5-208, telephone 202-473-7596, fax 202-522-1735, email address lwang1@worldbank.org. April 2002. (33 pages)

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Health Outcomes in Low-Income Countries and Policy Implications:

Empirical Findings from Demographic and Health Surveys

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1. Introduction

To improve health outcomes in poor countries and for poor people within these counties, efforts have been directed in two areas. First, a large number of empirical studies have focused on improving our understanding of the key determinants of health outcomes and identifying the principle causes of the health gap between the poor and the better off. Secondly, a strong emphasis has been placed on translating empirical findings into effective policy interventions. Gwatkin (2000) provides a critical reflection in these two areas and summarizes key policy actions taken by major international development agencies. Wagstaff (2001) presents an overview of the research findings on the relationship between poverty and health, with special attention being focused on how to explain these findings and how to design polices to improve health outcomes in low-income countries.

There is a renewed focus in the policy debate on health inequalities. This results directly from the increasingly strong advocacy for defining poverty in the context of human development to broaden the traditional income/consumption definition of poverty. Wagstaff (2001) reviews trends in health inequalities both in developed and developing countries, identifies the causes of inequalities, and proposes approaches for evaluating the impact of anti-inequality polices. The World Bank (2000) has compiled the most comprehensive indicators on socioeconomic differences in health, nutrition, and population based the Demographic and Health Survey (DHS) data, which provide useful inequality measures in health.

However, to better understand the determinants of health outcomes, it is essential to measure health outcomes as well as inequality in health using reliable data sources. One of the major concerns in carrying out a cross-country analysis on health is the reliability as well as comparability of data sources, both across countries and over time. Srinivasan (1994) has critically reviewed the potential problems associated with cross-county data. This problem is particularly acute for the estimates of child mortality rates as their measurement is sensitive both to the types of data sources used and the estimation methods. Filmer and Pritchett (1996) summarize that child mortality estimates completed by the United Nations show substantial discrepancies among different estimates for the same county and same period, depending on data source and the choice of estimation method. This implies that in producing credible empirical evidence on health issues using cross county data we should pay special attention to data comparability and estimation method. In this regard, demographic and health surveys, which have been conducted for over 60 low-income countries since 1985, are a superior data source. They are comparable across countries and use the same methodology to estimate health and other socio-economic indicators, both at the national level, and for urban and rural areas separately. Therefore, empirical studies on health determination based on the DHS data are expected to generate more reliable results.

Moving from research findings to operational actions requires designing policy interventions with a strong poverty focus. These interventions should be effective both at improving the overall average level of health (i.e. efficiency) and at narrowing inequalities in health (i.e. equity). In reality, policy design often needs to take account of trade-offs between efficiency and equity in health. However, to provide more informative policy recommendations, empirical analysis of health needs to be conducted at a disaggregate level, by socio-economic group, or by geographic location, when data permits. The emphasis of a rural/urban separation is particularly useful from the policy perspective as the geographical distinction is often a more useful targeting indicator than income quintiles. In addition, both the level and distribution of household access to basic services such as safe water, sanitation, infrastructure, and health facilities, vary sharply between urban and rural areas. Given that the poor are mainly concentrated in rural areas, it is likely that the determinants of health differ for rural and urban population. Therefore, identifying determinants of health outcomes for the poor and non-poor separately can potentially improve the effectiveness of policy interventions.

This study aims to identify key determinants of health outcomes in poor countries both at the national level, and for rural and urban areas separately, for the purposes of selecting effective health interventions. We focus on two health indicators, the infant mortality rate (IMR) and the under-five mortality rate (U5MR). The primary data sources are the DHS and World Development Indicators.

A large body of empirical studies that focus on identifying the determinants of health outcomes are based on data sources of various forms. These include (1) cross-country data sources (Pritchett and Summers, 1995; Filmer, King and Pritchett, 1998; Filmer and Pritchett[2] ,1999; Rutstein[3], 2000; Shi, 2001); (2) cross-region data for a given country (Murthi, Guio and Dreze, 1995; Dreze and Murthi ,1999), and (3) household-level surveys including DHS and Fertility surveys (Hughes and Dunleavy, 2000; Jyotsna and Ravallion, 2000, Claeson, Bos, Mawji and Pathmanathan, 2000; Wagstaff, 2001).

In comparison to earlier cross country studies, the main contributions of this study lie in the following: (1) use of the improved data source on health from DHS; (2) investigation of health determinants both at the national level and disaggregated by urban and rural location; and (3) the application of the regression estimates to an effectiveness analysis for selection among alternative policy interventions.

This paper is organized as follows. Section 2 provides an overview of the patterns in health outcomes in low-income countries. In section 3 we discuss the major data issues and summarize the data sources used in this study. Section 4 focuses on issues related to estimation methods. Section 5 presents the main findings. Section 6 illustrates the application of the estimation results to an effectiveness analysis. Section 7 concludes.

2. Patterns of Health Outcomes in Poor Countries

To capture the general patterns in health outcomes using comparable DHS data sources, we focus on two health measures: (1) the level of healthiness and (2) inequality in health.

[2] Pritchet and Summers' data source on IMR and CMR5 is based on UNICEF data; child mortality data used in Filmer and Pritchett's study (1999) is from the UNICEF and WBI (1997).
[3] The national level indicators constructed from DHS surveys

Child mortality rates, are generally regarded as the principle measures of country-level health status,[4] although more comprehensive measures would also include indicators measuring morbidity. However, the latter measures tend to be less reliable and in most cases, are less comparable across countries. Inequality in mortality is measured using the concentration index (CI).[5]

Child mortality and CI constructed from DHS data for over 60 low-income countries between 1990 and 1999 reveal two striking observations. First, we find a strong negative association between the level and inequality in child mortality as captured in Figures 1 and 2. In general, countries with high mortality rates tend to have low levels of inequality in mortality, and vice versa. This observation seems to suggest that if policy interventions were successful in reducing child mortality over the past decade or so, they may largely have reached better off households among low-income countries.[6] However, to assess how successful policy interventions are on equity ground, we need information which enables us to trace countries over time and test if the changes in mortality rates differ significantly between the poor and non-poor for any given country. Unfortunately, estimates of mortality and inequality in mortality by income group from the DHS are only available at one point of time for each county. Given this constraint and the fact of high concentration of the poor in rural areas, we illustrate this point using changes in mortality disaggregated by rural/urban location for individual countries. Table 1 summarizes changes in child mortality for countries with at least two observations for the 1990s by geographic location.

The second observation, as shown in Table 1, is the significant differences both in level and changes in child mortality between urban and rural areas. The numbers presented in Table 1 show a significant gap in child mortality between rural and urban over the course of the past decade. At the beginning of the 1990s, IMR and U5MR were 87 and 143 per 1000 births in rural areas, both figures are much lower in urban areas, being 67 and 105 per 1000 births. However, despite the initial higher mortality in rural areas compared with that in urban areas, over the course of the 1990s, the rural population had experienced a much smaller reduction in child mortality. The annual rates of reduction in IMR are 1.7% and 2.1%, and in U5MR are 2.1% and 2.6%, for rural and urban areas, respectively. Together, these two piece of empirical evidence strongly suggests that, across low-income countries, health interventions implemented in the 1990s may not have been sufficiently effective at targeting the poor. However, we should note that to reach more solid conclusions on the distributional impact of health interventions requires rigorous policy evaluation, which is beyond the scope of this study.

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[4] Life expectancy is another important indicator, but its estimate is also based on the mortality rate.

[5] The concentration index, which is similar to Gini coefficient, is defined as the ratio of the area between the concentration curve and the diagonal to the area under the diagonal. The concentration curve is constructed by plotting the cumulative proportion of child deaths (on the y-axis) against the cumulative proportion of children (on x-axis), ranked by economic positions (income or other measures of welfare) of the household to which they belong. Wagstaff (2000) provides a simple and intuitive description of the concept of the CI.

[6] However, it might also be possible that while all segments of the population experienced an improvement in health, the better off had a bigger reduction in mortality rates, in which case, we would also observe the patterns of a negative association between mortality and inequality.

Note also that countries that are off the general trend between the level and inequality in child mortality deserve special attention. Important lessons can be learned from these "outliers", including both the better performing countries (lower-than-average in mortality and inequality measures) and the worse performing ones (higher-than-average in both). Ranked in descending order, the former group includes China, Ghana, Guatemala, Namibia, Nicaragua and Zimbabwe, and the latter group consists of Cameroon, Central African Republic, Cote d'Ivoire, India, Madagascar and Mozambique.

Several key policy questions arise from the above ranking. First, what policy interventions have helped to produce win-win results, i.e. low mortality and low inequality, as observed in China. Secondly, why are almost all poor performing countries located in Africa, with the exception of India? Even among the poor performing African countries India was ranked low in the list. The China and India comparison is particularly interesting from a much broader development perspective. Despite their similarity in the initial level of development, including population structure, and key socio-economic indicators, development outcomes of the two countries are strikingly different. This fact is a fundamental development issue in itself as pointed by Dreze and Sen (1995, 2002). However, to address such important questions in depth, we need to supplement the cross-country analysis with county specific studies on China and India.

3. Data

Why use DHS

As highlighted in the introduction, data comparability is particularly important in conducting cross-county analysis of health outcomes. The main reasons lie in the statistical fact that principle health outcome indicators, such as child mortality rates are sensitive both to data sources and estimation methods.[7] A recent UN report has provided a compilation of mortality rates estimated using different data sources and/or different estimation methods.[8] Table 2 summarizes the scale of discrepancy in mortality rates for selective countries. The figures illustrate clearly the degree of sensitivity of mortality rate estimates. For example, using two different data sources, under-5 mortality rate for China in 1991 ranges from 34 to 61 per 1000 births. Hence, the credibility of the empirical results, in particular based on cross-country data on health outcomes, depends crucially on the availability of a database with health indicators estimated using common methodology and comparable data sources such as DHS.

[7] There are principally two methods used to estimate mortality rates , namely direct and indirect methods. The former use complete maternal history information, while the latter is based on incomplete maternal history and implemented by imposing several assumptions, including (1) homogeneity of mortality risks by age group of mother, (2) stable fertility patterns, and (3) children being exposed to the same mortality risks, regardless of the mother's age (United Nations, 1992).

[8] In the database handbook for developing countries produced by the UN (1992), discrepancies between the direct and indirect estimates of child mortality rates are observed for many countries.

The DHS uses identical survey instruments across countries and estimates mortality rates using a consistent method[9]. The DHS are nationally representative, hence a wide range of basic population indicators (in addition to mortality rates) can also be constructed from this data source. These indicators include basic household socio-economic characteristics, fertility information, child nutrition status, and household access to services (safe water, sanitation, and electricity), utilization of basic health and education services, mother's education and knowledge of treatment of common child illnesses. These basic indicators are derived by applying expansion factors, so they are estimates of population indicators for each country. The comprehensive coverage of the basic population indicators provides us with a good opportunity to relate population health outcomes to possible key determinants. Recently, Macro International has published all basic indicators for 60 countries between 1985 and 1999, both at the national level and for urban and rural areas separately.

To estimate child mortality rates, in addition to demographic surveys, two other primary data sources can also be used: (1) vital registration system data, and (2) census data. In general, the vital registration system is not a reliable data source for developing countries as the magnitude of incomplete registrations can be substantial, thus resulting in significant measurement errors in the mortality rates (UN, 1992). Thanks to the recent efforts from international organizations and national statistics offices in many developing countries, a large number of countries are now able to conduct censuses periodically (every 5 to 10 years), which provide an important data source for estimating mortality rates at the national as well as regional level for a given country.[10] But censuses are limited in their coverage on socio-economic variables and, therefore, it is not always possible to use censuses to address such issue as determination of health outcomes.

In contrast, DHS is an improved data source. But the sample size in DHS is relatively small for conducting regional level (within a country) analysis on health. Empirical studies focusing on explaining regional variations in health outcomes can often be more informative in guiding county-specific policy design, while results from cross-country analysis are generally useful for formulating global strategies. Given there are limitations in all data sources as outlined above, one possible solution is to combine censuses with DHS for conducting regional analysis on health outcomes. Recent work by Hentschel, Lanjouw, Lanjouw and Poggi (2000), and Elbers, Lanjouw and Lanjouw (2000) has developed a methodology of combining censuses with household surveys for poverty analysis, and the empirical evidence of their studies have demonstrated encouragingly that it is possible to apply the developed methodology to areas beyond poverty analysis, e.g. to include health and environment issues.

[9] Since these surveys collect complete maternity history, child mortality rates can be estimated based on complete maternal history for all women in the DHS.

[10] Only a third of low-income countries have had a census since 1985 and 27 per cent of LDCs have a latest census that was conducted prior to 1975. As a result, infant mortality for many developing countries before 1990 are based on interpolations and extrapolations, and therefore, are not measurements (Deaton, 1995; Chamie, 1994).

Variables

Despite the many advantages of the DHS over other data sources, one of its limitations is the absence of income or expenditure variable, which are generally regarded as good measures of welfare. Filmer and Prichett (1998) propose the use of a wealth index as a measure of welfare.[11] They also illustrate that the ranking of households by their economic positions based on the asset index are very close to that based on expenditure. However, in this study, the key objective is to select alternative policy interventions based on estimation of a health outcome model. To this end, an income variable is more easy to interpret than a wealth index, when comparing with other policy variables such as improvement in access to safe water or sanitation, or female education. To overcome the problem of lack of income in DHS, we supplement the DHS data using WDI data which provides a country-level time series of economic and social indicators, including GDP per capita and public expenditure on health. To ensure consistency, we attempt to use variables derived from the DHS to the extent possible and only resort to other sources when key variables are not available from the survey.

Table 3 summaries all variables from DHS and WDI used in the estimation of the mortality determination model. However, several variables, which are either constructed specifically or chosen for specific reasons, deserve a separate discussion.

<u>*IMR and U5MR*</u> The mortality rates are estimated using a five-year period analysis approach. By this method, IMR and U5MR are estimated using maternal history several years preceding the survey year (e.g. 0-4, 5-10 or 11-15 years preceding the survey date). We use the most recent estimates of mortality rates, i.e. 0-4 years preceding the survey date. There are two advantages in using the estimates nearest to the survey year (0-4 years). First, the mortality rates can be regarded as a measure of average health outcomes for the period between the survey date and five years prior to the survey. Secondly, the measurement errors in mortality rates due to misreporting can be reduced, to some extent, when using the more recent maternal history data.[12]

<u>*GDP per capita*</u> We use real GDP per capita at constant prices in the estimation and match this income variable to corresponding child mortality rates constructed from the DHS. GDP variables from the WDI are purchasing-power-parity adjusted and expressed in current international dollars. To control for inflation (as the dates of DHS vary across countries), we then convert all incomes into constant prices using the US CPI as the deflator (1995 US CPI=100). In order to investigate the effects of both current and lagged

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[11] Using principle component analysis, a wealth index can be derived by combining information from housing characteristics and possession of household durable goods.

[12] Our estimation of mortality rates for China shows clear evidence of downwards bias in IMR using retrospective questionnaires as respondents are more likely to treat the incidence of child death as never born, the longer the duration between the survey and time of the incidence. Using the 1992 China Children Survey, the estimated IMR for rural and urban areas between 1987-1992 are as follows:

	Rural	Urban	Total
1987-88	21.1	13.9	19.6
1989-90	22.1	13.5	20.3
1991-92	32.1	13.7	28.1

The increasing trend of IMR in rural China is inconsistent with estimates from all other sources which show a consistent fall of IMR in rural areas over time.

incomes on health, we construct several sets of GDP per capita variables: (1) five-year moving average (MA) corresponding to the survey year, and (2) its lags.[13]

Share of health expenditure in GDP The information on the share of health expenditure is only available periodically for most countries from the WDI. Therefore, including health expenditure in the model can lead to a sharp reduction in sample size for the estimation. To minimize the loss of observations, we therefore use a five-year average of health expenditure shares for countries for which no corresponding health expenditure data at the survey date is available. Such construction is reasonable as public expenditure tend to move with GDP, and consequently, the shares of government expenditures remain relatively stable over time.

Per capita health expenditure Information on per capita health expenditure from the WDI is available for most DHS countries from 1990 to 1998. We construct a three-year moving average of health expenditure to match the DHS survey years, and for countries that have no health expenditure data for the corresponding years, we use the average over the total period of 1990-98.

Asset index Asset index is constructed using simple weighted average of proportion of households that own individual durable goods.[14] We include all key durable goods relevant for urban and rural households, respectively and give equal weight to each item.

Choice of Counties in the Sample

DHS started in 1985, but the survey questionnaires have became more uniform and comparable since 1990. For example, surveys conducted prior to 1990 do not have detailed information on access to services (e.g. access to electricity), and the questionnaires were not sufficiently uniform across countries to allow us to estimate the health determination model. Therefore, we use only surveys from 1990 onwards. On average each country has two surveys thus we have a database containing cross-section and time-series observations.

In all earlier cross-country studies, China had been a missing observation due to unavailability of Chinese demographic and health surveys. But China is important both in terms of its population size and health outcomes. The recent release of the 1992 China Children Survey[15] makes it possible to add China to our database. With the inclusion of

[13] To illustrate the procedure with an example by assuming the DHS survey year is 1995. There are two steps: (1) convert all GDP per capita into constant international $; and (2) construct moving average GDP_{90-95} using GDP per capita between 1990-95, and its lags (MA GDP_{85-90}) using GDP per capita between 1985-90.

[14] This method, which is similar that used for constructing human development index by the UN, is by no means the perfect way of deriving index variable. However, our asset index suffers less the problems associated that used in human development index as all components share some common features and the asset index is a simply monotonic function of all arguments included. The choice of equal weights are arbitrary, but in the estimation, we test the sensitivity of our results to the choice of different weights.

[15] The 1992 China Children Survey is a national survey which uses similar survey instruments as that of DHS. The estimates of mortality rates are directly comparable to that from the DHS.

the China survey in the sample, the population coverage of low-income countries from the sample increases by nearly one fifth.

The data set used in the regression is effectively an unbalanced panel. The number of repeated observations for a given country are not uniform across countries and the survey years vary by country. Given these constraints, we pool all surveys together. However, the pooling of all observations implicitly assumes that the health outcomes are independently distributed across countries and over time. The latter is hard to defend given that many variables at the country level tend to be auto-correlated over time. In the estimation, we relax this assumption and allow observations within each country to be correlated[16].

4. Estimation

To empirically estimate the health determination model, we need to address issues related to the model specification. We begin with a model specification for health determination by considering health outcomes as a function of key groups of variables (similar to that in Filmer and Prichett, 1999). Our choice of explanatory variables are based both on economic theory and empirical evidence from earlier work in this area. These include: (1) incomes; (2) various social and environmental indicators, including the level of female education, access to sanitation, access to safe water; (3) policy variables such as the share of public health expenditure in GDP or immunization coverage; and (4) country-specific effects, e.g. the level of urbanization, the quality of government and cultural effects. Such a grouping has an advantage with respect to our intended cost-effectiveness analysis, as we can compare various alternative interventions, e.g. improving access to female education versus improving access to sanitation when cost data are available. A more detailed discussion on this is deterred to section 6.

The basic relationship can be summarized as follows:

$$\begin{aligned} \textit{Mortality Rates}_{it} = {} & \alpha^{*}\textit{Income}_{it} + \beta^{*}\textit{Social Indicators}_{it} + \eta^{*}\textit{ Policy Instruments}_{it} \\ & + \delta^{*}\textit{Country Specific Effects}_{i} + \varepsilon_{it} \end{aligned}$$

where ε_{it} is the error term, following an identical and independent distribution.

We focus our discussion on three aspects of the model specification. These include: (1) the possible two-way causation between health outcomes and included explanatory variables such as income or government health expenditure; (2) the third variable effect, i.e. unobservable variables that may affect both income and health outcomes, e.g. quality of government; and (3) the existence of heteroscedasticity and the effect of outliers.

These concerns related to model specification, to some extent, can be dealt with by employing different estimation methods when data requirements can be met. For example, use of an Instrumental Variable estimator (IV) can deal with issue (1) if we are

[16] We use an estimation method which allows cluster effects.

able to find valid instruments[17], Fixed Effect estimation can solve the problems associated with issue (2) if we have repeated observations for each country, and a Weighted Least Square (WLS) estimator can help reduce the effects of outliers as discussed in (3). In the following, we discuss these three aspects of the model specification outlined above in the context of the estimation methodology.

4.1 Two-way causation

It is often argued that the robust positive correlation between health and income observed in either cross-country or household-level data can be interpreted in two ways. As put by Pritchett and Summers (1996): "wealthier is healthier" or "healthier is wealthier"? At the international level, the evidence of a causal relationship between incomes and health is inconclusive. To establish the causation, Pritchett and Summers (1996) have carried out a thorough and extensive econometric analysis using a range of valid instrumental variables that could be found and they conclude that there exists strong evidence in favor of a causal and structural relationship running from income to health outcomes. Using a similar approach, Filmer and Pritchett (1999) find no evidence supporting the two-way causation between health outcomes and public health spending based on DHS data. These studies have direct implications for our choice of estimation methods. In empirical analysis, finding valid instrumental variables can be a formidable task on the one hand, and on the other hand, any benefits derived from using IV can often be offset by its weak inference power as the estimates of the standard errors from IV are usually much larger than that from OLS.

In reality, the impact of income on health is not instantaneous. It takes time for the income effect to be fully transmitted into health outcomes, in particular at the national level. Therefore, it makes sense to relate lagged incomes to current health outcomes.[18] In the following analysis, we use five-year moving averages of GDP per capita (five years preceding the DHS survey year for each country) and relate it to the mortality rates estimated from the corresponding DHS. Such a specification, to some extent, can avoid the problem of two-way causality if it indeed exists. In light of the above empirical evidence from the earlier studies and econometric considerations, we start our specification assuming the causation running from incomes and public health expenditure to health outcomes.

4.2 Third variable effect

Country-specific effects, such as the capacity of government to manage and deliver health services, can affect both incomes and health outcomes simultaneously. However, these third variables are not always observable or quantifiable. If the third variable is country specific and time invariant, consistent estimates of the health model can be obtained using either first-differencing or fixed-effect estimation. However, given that only 28 countries in our sample have repeated observations, the sample size limitation implies that the proposed estimation methods can not be empirically implemented. To

[17] Valid instrumental variables are those that are highly correlated with the explanatory variables concerned but not directly related to the health outcomes.

[18] Using DHS data, Hill and King (1992) find strong effects of lagged female enrollment on infant mortality.

partially deal with this issue, we include in our model the share of rural population for each country to act as a proxy variable for country-specific effects.

4.3 Heterogeneity and Outliers

It is highly possible that the sample estimates of IMR and U5MR may have a different variance across countries and over time. The existence of heteroscadasticity in the error terms, however, does not pose a serious problem in terms of obtaining consistent estimates, as it only causes a bias in the estimates of standard errors, which can be corrected using robust-t statistic estimates. But it is important to control for the effect of outliers which can significantly bias estimates. In the following estimation, we control the influence of outliers in two ways. First, we estimate health models using both OLS and WLS methods to check the consistency of the estimates. Secondly, we estimate the above model by sequentially deleting one country each time to examine the robustness of estimates to the exclusion of individual countries.

The ultimate objective of our empirical analysis is to identify all principle health determinants and apply the estimated coefficients to an effectiveness analysis. Naturally, we should start our model specification by including all "legitimate" exogenous determinants of health outcomes. However, in the empirical analysis, we need to consider the problem of multicollinearity due to the nature of cross-county data, which typically has small sample size and high correlations among the explanatory variables. This implies that we need to be selective in the choice of explanatory variables in order to minimize the bias caused by omitted variable specifications. In the regression analysis, we experiment with different model specifications to check the robustness of the results.

5. Results

We first investigate the simple bivariate association between mortality rates and all potential explanatory variables. The correlation matrices are summarized in Appendix Table 2a-2c. At the national level, variables which are highly correlated with mortality rates, ranked in descending order, include access to electricity, asset index, GDP per capita, access to piped water, access to sanitation, and female secondary education. However, the ranking is different at the disaggregate level. In the urban data, mortality is highly correlated to access to electricity, asset index and female secondary education, while in rural areas, access to piped water, access to electricity, female education, asset index and vaccination coverage are closely related with mortality. The rankings are nearly identical for IMR and U5MR, which is not surprising given the high correlation among the two indicators (over 0.92). To estimate the net impact of individual variables on mortality, we use a multivariate regression approach to control for the possible correlation among the explanatory variables. In the following, we estimate the health determination model of IMR and U5MR using data both at the national level and disaggregated by urban/rural sector.

<u>*Results for IMR*</u>

Table 4a summarizes the regression results for IMR. At the national level, the regression results show that several factors are identified to have a significant and robust impact on mortality, after controlling for all other variables. These include incomes, health expenditure, access to sanitation (flush and pit toilets), access to electricity, and vaccination coverage in the first year of life. The aggregate data fit the model well with about 88% of the variation in IMR being explained by the included variables. But, variables such as female education and access to safe water, that were often found to play an important role in determining IMR in earlier empirical studies, are not statistically significant in our results.

The focus of this study is to go beyond the national level by conducting analysis also for urban and rural areas separately. However, two key health determinants are not available in the disaggregated data for rural and urban areas (1) incomes and (2) public health expenditure. To obtain rural/urban incomes for each country we need to use other household survey such as Living Standard Measurement Survey (LSMS) data to match with the DHS data. However, this task can be particularly difficult to accomplish as it requires converting rural and urban incomes into a comparable base using a rural/urban price index, which is available for very few countries. In light of this data limitation, we chose to include in the model a proxy variable for income, the asset index which summarizes durable goods ownership. From the DHS data, the proportion of households that own different consumer durable goods (TV, refrigerators, radio, bikes, motorbike among others) can be estimated for urban and rural areas separately. We then construct the asset index by a simple weighted average of key durable goods.[19]

Regarding health expenditure variable, we chose to include the share of health expenditure of GDP at the national level in the urban and rural regressions. But this leads to a change in the interpretation of the health variable. We effectively examine how rural and urban health outcomes are affected as average health expenditure shares change.

The regression results at the disaggregate level (Table 3a) differ significantly from that generated using the aggregate level data. In urban areas, we find that access to electricity, in particular, has a large impact on IMR, although asset index, and health expenditure share are also statistically significant. But, other key health determinants such as female education, access to safe water, access to sanitation, and vaccination coverage have no significant effect on IMR, either individually, or jointly (the joint significance test, $F(6,33)=0.85$).

In the rural result, none of the included variables is statistically significant, except that access to electricity is significant only at the 10% level. The joint significant test on female education, access to safe water, access to sanitation, and vaccination coverage show that these variables jointly have a significant effect on reducing IMR in rural areas ($F(5,31)=4.63$, significant at 1%). It is also interesting to observe that that increasing the average share of health expenditure of GDP, reduces IMR in urban areas, but not in the rural areas (although it has the right sign).

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[19] We check the sensitivity of our estimates to different sets of weights, and find little changes in the results with respect to different weights. The following formula are used to construct the asset index:

asset_urb= 0.2*tv_urb + 0.2*frig_urb +0.2*radio_urb +0.2*bike_urb+0.2*mot_urb

asset_rur= 0.2*tv_rur + 0.2*frig_rur +0.2*radio_rur +0.2*bike_rur+0.2*mot_rur

The results from the disaggregated data on IMR are unexpected. There might be two possible explanations. First, the results could be a true reflection of reality. Given the medical evidence that most infant deaths occur in the first month of birth, it may well be true that interventions in antenatal care might be the only relevant factor explaining IMR and therefore, the included variables are expected play little significant role in explaining IMR. Only a few countries with DHS has collected information on access to antenatal cares, therefore, the inclusion of this variable greatly reduces our sample size and the results are directly comparable with that produced without including this variable as reported in Table 3a.[20] To include access to antenatal care in the model, we find that it has a significant impact on IMR in urban areas (coefficient -0.31; t(2.2)), but has no significant impact in rural areas, nor at the national level.

The second explanation for the unexpected IMR results is a statistical one. The pattern of the results at the disaggregate level, is quite striking – the models have very high explanatory power, with R^2 being 0.77 and 0.68 for urban and rural areas respectively, yet with few significant estimates. To some extent, this suggests the existence of strong multicollinearity, which is a typical feature of cross-county data. One of the major limitations in the cross-country analysis lies in the difficulty of empirically estimating the independent effect of key variables, mainly due to relatively small sample size. Given the problems of high correlation among these variables, in the first stage of the analysis we carry out extensive experiments to check the robustness of the results with respect to choice of explanatory variables. We find that although the estimated coefficients are quite sensitive to the inclusion of a few highly correlated variables,[21] they remain relatively stable to the variables listed in Table 3. Nevertheless, to produce robust empirical evidence for the purpose of designing policies it is necessary to move beyond the cross-country analysis, and conduct empirical studies using the sub-national level or household-level data whenever possible.

Results for U5MR

The estimation results for U5MR are reported in Table 4b. At the national level, income, health expenditure share of GDP, access to electricity, vaccination coverage in the first year of life, access to sanitation (pit toilet latrine) *each* has a significant impact on reducing U5MR. To a large extent, the results for U5MR are similar to that for IMR, except that most of the estimated coefficients are much larger in the former model. For example, the impact of access to electricity on U5MR is almost three times that of IMR (the coefficient being –1.02 for U5MR, and –0.36 for IMR for urban data; -0.97 for U5MR and –0.32 for IMR, for rural data), indicating that health interventions focusing on improving household access to electricity could be a very effective policy for reducing U5MR, but not necessarily so for IMR.

In urban areas, we find that access to electricity is the only important determinant of U5MR, controlling for all other variables. But asset index, health expenditures, female

[20] Note the inclusion of the antenatal care reduces the sample size from 48 to 22 for urban data, 46 to 28 for rural data, and 41 to 26 for the aggregate data, hence these results are not directly comparable with those reported in Table 4a.

[21] When including both male and female education, or all types of access to water and sanitation, the regression results are very unstable.

education, access to piped water, flush toilets, and pit toilets latrine jointly affect U5MR (joint significance test, F(8,32)=2.20, significant at the 10% level). In rural areas, however, vaccination coverage is an important factor which reduces child mortality (access to electricity is significant at the 10% level). It is interesting to observe that increasing the share of health expenditure of GDP at the national level significantly reduces the U5MR in rural areas, but not in the urban areas, while the opposite is observed for IMR.

We should emphasize two issues that are related to public health expenditure variable included in the above estimation. First, how we can best measure public health expenditure, i.e. choosing between the share of health expenditure of GDP and per capita health expenditure (expressed in PPP$). Secondly, some of the included health determinants (vaccination coverage and mother's knowledge of ORS) could be regarded as the outcomes of public health expenditure, therefore, estimation problems arise when treating them as covariates in the model specification as in above estimation. To deal with the first issue, we repeat all estimations replacing health expenditure shares by per capita health expenditure. We find hardly any differences in the two sets of estimation results, except that per capita health expenditure is never statistically significant. So we choose the share of health expenditure in the final results. To test if some of the included variables are outcomes of the public health expenditure, we compare estimation results from models with and without including health expenditure variable. No evidence is found to warrant the second concern of the health expenditure variable. The results show that health expenditure and other included variables have independent impacts on health, i.e. all estimates of RHVs are very robust to the exclusion of health expenditure variable.

We also test the robustness of the results to outlier effects. This is done in two ways (1) using the Weighted Least Square estimator[22] and (2) performing regression analysis with deleting one country in the sample sequentially. The WLS results (not reported) for IMR are very close to that using the OLS, while the estimated coefficients for U5MR change marginally depending on the choice of weighting variables.[23]

The regression results from deleting one country sequentially in the sample appear relatively stable. The range of the estimated coefficients are reported in the note of Table 4a–4b. The following discussion focuses only on those "interesting" coefficients, i.e. that are significant and have the right sign. The estimated effect of access to electricity on U5MR in urban areas changes from -1.15 (dropping Namibia) to -0.86 (dropping Zambia). The coefficient of vaccination coverage in the rural data varies from -0.86 (dropping Brazil) to -0.52 (dropping Nicaragua). With regard to IMR, the estimated coefficient of access to electricity in urban areas ranges from -0.28 to -0.42. The above results suggest that the issues of heterogeneity and the effect of outliers are of secondary concerns which, to a great extent, enhances our confidence in the findings based on OLS method.

[22] The weighting variables using GDP per capita, square root of population size, and their inverses.
[23] The effect of breastfeeding seems to be less robust to the choice of estimation methods and weighting variables. When using GDP or the inverse of population as weights, breastfeeding variable becomes significant, but it is insignificant with the inverse of GDP or Population as the weighting variables.

Access to Electricity

The finding that access to electricity has the largest impact in reducing mortality in comparison to all other policy interventions (access to sanitation or safe water) is particularly interesting. This finding is new as none of the earlier studies have identified the electricity effect, partially due to data limitations. But why can connecting households to electricity produce important health outcomes among low-income countries? One possibility might be that, in the case of the urban and rural results, we do not have the income variable and our constructed asset index may not have captured the income effect fully, thus having access to electricity is, in fact, a proxy for incomes. Therefore, it may be picking up the income effect.

To empirically separate the electricity effect from income, we use data at the national level where we have all three variables concerned: income, asset index, and access to electricity. Table 5 summarizes our results for verifying electricity effect. The estimated coefficient for access to electricity is hardly affected by adding income variable in the model specification, after controlling ether only for asset index (mod-1 vs. mod-2) or all other relevant variables (mod-3 vs. mod-4). Note that asset index and access to electricity have the same level of correlation with income (0.80 and 0.93, respectively)[24], but the estimated coefficient of asset index (not significant) is affected with the inclusion of the income variable. This indicates that access to electricity is likely to be independent of incomes. Not only has the access to electricity an independent effect on mortality, it is also a key underlying factor explaining mortality. This variable alone accounts for about 64% of variations in U5MR (mod-1), surpassing the income variable (mod-6) which explains 61%, while all included variables account for 72% of the variation in U5MR.[25] The coefficient for the asset variable is not significant with or without introducing incomes in the specification (mod-4, and mod-5).

The above evidence indicates that access to electricity indeed has a significant and independent (of income) impact on mortality. It is possible that households linked to electricity may be more likely to use electric appliances (such as refrigerators, microwaves, or kettles) or have access to hot water. These in turn can facilitate household hygiene practices, hence reducing the possibility of contracting infectious diseases, in particular among young children. Given the immediate implications of such findings for operations and policy design, further research, in particular using regional-level or household-level data for individual countries, is needed to verify the effect on mortality of linking households to electricity.

In light of the new findings on the important electricity effect on mortality, it is useful to revisit the income impact on health, which has been the strong emphasis in earlier studies. Our results suggest that the income effect on health may have been grossly overestimated in early cross countries studies, stemming from model misspecification

[24] The asset index and access to electricity has a correlation of 0.92.

[25] In the urban results, asset index is significant, but access to electricity is robust to the inclusion of asset index, but, not vice versa. The electricity variable alone explains about 77% variation in U5MR, while all included variables explain 85% of total variation.

which omits access to electricity.[26] This conjecture is borne out by the comparison of the two specifications (mod-6 and mod-2) as shown in Table 6. We find that, when *not* controlling for all other variables, the estimated gross income effect is large (-70.5), but this coefficient is more than halved (30.5), once we add the electricity and asset variables to the model.

There exists plenty of empirical evidence indicating that other factors besides incomes are more important health determinants.[27] For example, Anand and Ravallion (1993) find the commonly observed health and income correlation vanishes once one controls for the incidence of poverty and public spending on health. Hence, they argue that empirical analysis on health issues should shift the focus towards factors beyond incomes in order to provide useful information for designing more effective and relevant policies. Our results provide additional support to this argument. Overall, empirical evidence seems to show consistently, that it is possible to identify a range of low-cost health interventions that are more effective in reducing mortality than polices which narrowly focus on increasing national incomes.

6. Effectiveness Analysis

In principle we can apply the estimated coefficients from the model of health determination to a cost-effectiveness analysis. The estimated coefficients provide measures of the ***net*** impact of each intervention (which corresponds to each explanatory variable), keeping all other impacts constant. In turn, the inverse of the estimates, which we label as the effectiveness coefficients, are particularly useful for comparing various alternative interventions. They provide a measure of what is required for each respective intervention in order to achieve an outcome of a unit reduction in mortality, after controlling for the effects of all other interventions. If we have relevant county-level information (such as household population, number of female of schooling age and etc) and the cost data on various projects designed for improving health outcomes including access to safe water and sanitation, it is possible to perform a cost-effectiveness analysis for the selection of different interventions. This is done by comparing the cost of each alternative intervention that produces the same outcome (e.g. an unit reduction of child mortality rate). The cost is calculated based on the cost of a project and the estimated effectiveness coefficients.

In reality, however, care should be taken in the implementation of the above approach. One of the main reasons is that it is not always possible to estimate precisely the net

[26] Almost all earlier empirical studies in this area, relate health indicators to income, a range of social indicators, and access sanitation and water, but never access to electricity.

[27] Factors which are identified as important determinants of child mortality include mothers' education and women's status (Summers 1992, Caldwell 1986), effective public programs (Dreze and Sen, 1991) and income distribution (Deaton 2001). Using cross-region data on India, recent empirical evidence shows that the income effect can be slow and weak, and that other personal and social characteristics, such as female literacy often have more powerful influence on demographic outcomes including mortality (Murthi and Dreze, 1995).

effect of individual variables due to multicollinearity and sample size limitation as illustrated in the above econometric results.

The underlying assumptions of our model specifications imply that the impact of each intervention has an uniform impact on mortality reduction regardless of the level of mortality. However, empirical evidence often suggests diminishing returns to interventions, i.e. interventions can have a much bigger impact on reducing mortality, the higher the mortality level. This suggests that a nonlinear functional form might better capture the impact on mortality of various policies. In the effectiveness analysis, we present results using both linear and nonlinear specifications[28]. As shown in Table 6, the estimated effectiveness coefficients from the nonlinear model are broadly in line with that from the linear model, except for income (with GDP growth rate being doubled in the nonlinear model) and access to sanitation.

Table 6 summarizes the estimated cost-effectiveness coefficients for various interventions to avert one infant and one child death per 1000 births. In the following discussion we focus only on statistically significant estimates from the nonlinear model. At the national level, to avert one under-five child death per 1000 births, there exist five possible alternative investments (expressed in percentage point): (1) to increase household access to flush toilets by 0.7; (2) increase access to pit toilet latrine by 2.7; (3) access to electricity by 0.6; (4) increase vaccination coverage in first year of life by 1.7; or (5) increase share of health expenditure of GDP by 0.2. In addition, macroeconomic policies which can produce an annual growth rate of per capita GDP, of about 6 per cent, can also achieve the same outcomes of mortality reduction. The interpretation of the health impact of GDP growth assumes growth does not cause worsening of income distribution, or no linkages between income inequality and health outcomes.

The numbers in the brackets summarize the two end point estimates for countries with the highest and lowest mortality rates. For example, Niger (1992) has the highest U5MR (318 per 1000 births), and Colombia (1995) has the lowest (23 per 1000 births). To reduce one under-5 child death per 1000 births, household access to electricity only nned to be increased by 0.2 percentage points for Niger, but 3 percentage points for Colombia. The results clearly illustrate the point that it is much easier to reduce mortality by choosing direct health interventions such as improving access to electricity, or expanding vaccination coverage than polices can produce an annual per capita GDP about 6%. According to WDI, the annual per capita GDP among LDCs between 1990-1999 is less 1%.

However, it should be emphasized that figures presented in Table 6 should be viewed as an illustration of the methodology, and not be taken too literally for policy purposes. The main reason is rooted in the limitations in cross-country data, as revealed in the econometrics results presented in the above section, in providing robust empirical

[28] We chose semi-log function so that the rate of mortality reduction of any intervention depends on the level of mortality and the cost-effectiveness coefficients. The numbers for the nonlinear model are calculated at the sample median, taking into account the fact that means are more sensitive to outliers than median.

evidence for policy design. Cross-county studies have their usefulness in capturing general patterns and trends in health outcomes at the global level, which is needed for formulating overall policy strategies.

7. Conclusion

The findings from the above cross-country analysis on health determination both consolidate results from earlier studies and add new evidence in this area. First, our results show that the disaggregate level analysis is more insightful than that focusing only on the national average. Secondly, factors that significantly affect child mortality rates differ between urban and rural areas. In urban areas, linking urban households to electricity has been singled out as one of the key factors reducing both IMR and U5MR. Using the national level data, we are able to show that the electricity effect on mortality is large, significant and independent of incomes. In rural areas, we find that expanding vaccination coverage significantly reduces U5MR. In general, the estimated impacts are much bigger for U5MR than for IMR. Thirdly, the above econometrics results indicate that despite our efforts in ensuring data comparability by constructing variables using comparable DHS, cross-county data in general have limitations in providing robust empirical results. Variables at the country level are often highly correlated, which makes it difficulty to disentangle individual impacts on mortality. This suggests that we should be cautious in deriving policy implications from empirical results based on cross-county data sources. In order to have a bearing on policy recommendations, future studies should focus on explaining regional variations in health outcomes based on sub-national data or household level analysis on health determination to supplement cross-country analysis.

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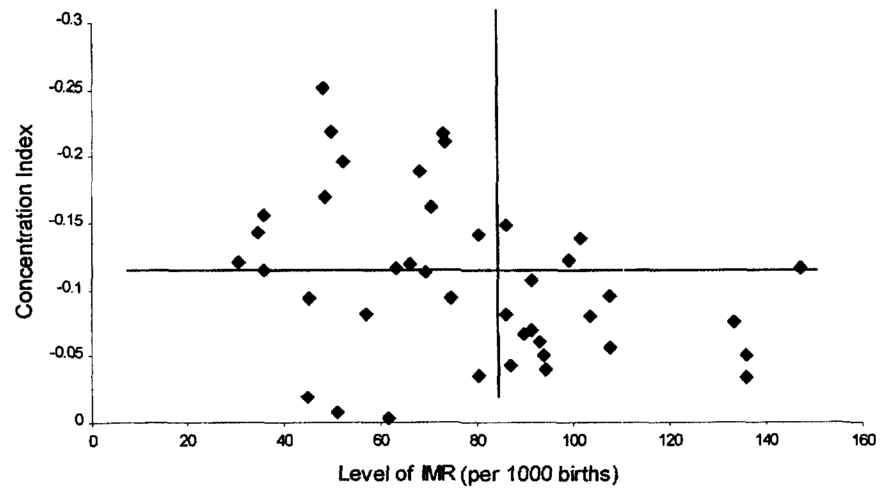
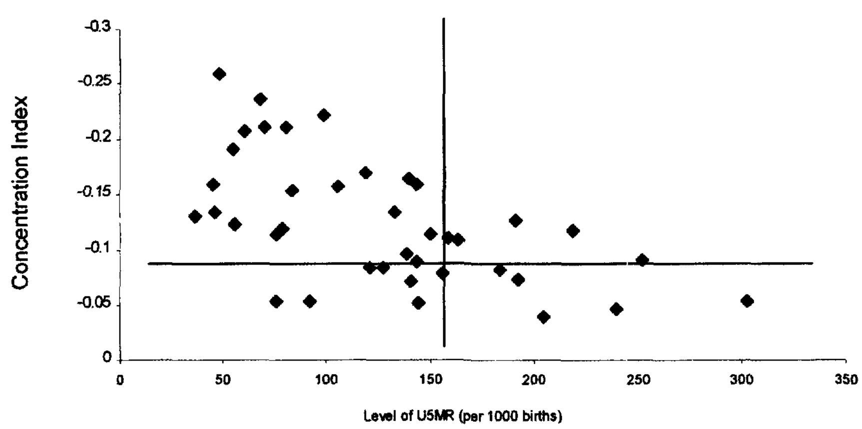
IMR: Level and Inequality



correlation=-0.33

U5MR: Level and Inequality



correlation=-0.59

Table 1. Urban/Rural Gaps in Mortality Rate: Levels and Decline Rates by Region

Region	***Country***	***Year***	***IMR***		***U5MR***	
			Rural	*Urban*	*Rural*	*Urban*
Africa	Cameroon	*1991*	86	72	159	120
		1998	87	61	160	111
	Niger	*1992*	143	89	347	210
		1998	147	80	327	178
Asia	Philippines	*1993*	44	32	73	53
		1998	40	31	63	46
	Indonesia	*1991*	81	57	117	84
		1997	58	36	79	48
	Bangladesh	*1994*	103	81	153	114
		1997	91	73	131	96
S. America	Brazil	*1991*	107	81	127	95
		1996	65	42	79	49
	Colombia	*1990*	23	29	34	36
		1995	35.2	28.3	43.2	34.1
Global Level	*All DHS countries*	*Early 1990s*	87	67	143	105
		End 1990s	77	58	126	89
	Decline Rate (%, per annum)		**1.7**	**2.1**	**2.1**	**2.6**

Source: The mortality rates are from the DHS website. The decline rates are estimated by the author.

Table 2. Summary of Estimates of Mortality Rates (per 1000 births)

Country	Reference date	Mortality rate	Data source
China	*1990*	43	10% sampling of the 1990 census
(U5MR)	*1990*	23	1% sample survey 1995, Indirect method
	1991	61	A large scale surveillance survey,1991
	1991	34*	1992 National Children Survey
Ghana	*1975*	*171*	*DHS 1988, direct method*
(U5MR)	*1975*	*154*	*DHS 1988, indirect method*
	1975	*130*	*Ghana Fertility Survey, 1980, direct method*
	1975	*125*	*Ghana Fertility Survey, 1980, indirect method*
Bangladesh	*1973*	*157*	*Bangladesh Fertility Survey,1975-76*
(IMR)	*1973*	*148*	*Contraceptive Survey, 1983-84*
	1973	*118*	*Contraceptive Prevalence Survey, 1979-80*

Source: United Nations, 1992; China State Statistics Bureau 1993.*

Table 3. Summary of Key Variables

Variable	*Definition*	*Mean*	*S.Dev*
$_1q_{0\_total}$	Infant mortality rate, national level (per 1000 births)	72	28
$_1q_{0\_Urban}$	Urban households (per 1000 births)	63	22
$_1q_{0\_Rural}$	Rural households (per 1000 births)	85	31
$_5q_{0\_total}$	Under-five mortality rate, national level (per 1000 births)	119	65
$_5q_{0\_Urban}$	Urban households (per 1000 births)	100	49
$_5q_{0\_Rural}$	Rural households (per 1000 births)	140	69
MA GDPpc	Five-year moving average of GDP per capita (ppp$, at 1995 price), (log), from WDI	7	1
MAruralpop	Five-year moving average of share of rural population (%), from WDI.	61	19
MAhexpshare	Share of health expenditure to GDP (%), from WDI. This variable is replaced by a five-year moving average of the share of health expenditure for countries that do not have health expenditure data matching the mortality data at survey year.	5	2
MAHexp_pca	Three-year moving average of per capita health expenditure (ppp $), from WDI. For countries where no health expenditure data is available for the corresponding DHS, we replace the observations by the average of health expenditure between 1990-1998.	105	107
prim_totf	Percent of household population with female age 6 and over having primary education (%)	40	16
sec_totf	Percent of household population with female age 6 and over having secondary education (%)	18	16
breastfed2_3	Proportion of children who were breastfed for 2-3 months, (%)	23	22
pipewat_tot	proportion of households having access to piped water, national level, (%)	43	23
wellwat_tot	proportion of household having access to well water, at the national level, (%)	31	21
surwat_tot	proportion of households having access to surface water, national level, (%)	20	17
flustoil_tot	proportion of households having access to flush toilets, national level, (%)	23	24
pittoil_tot	proportion of households having access to pit toilets latrine, national level, (%)	44	27
elec_tot	proportion of households linked to electricity, national level, (%)	40	32
vacc_tot	Percentage of children who had received all vaccines by the time of the survey,national level, (%)	52	19
vacc1year_tot	proportion of children vaccinated in the first year of life, national level, (%)	36	18
Ass+B12index_urb	Index for possession of durable goods for urban households, (%)	32	19
Assindex_rur	Index for possession of durable goods for rural households, (%)	22	14
Assindex_tot	Index for possession of durable goods for all households, (%)	25	15
knowORS_tot	proportion of women who have knowledge about oral rehydration, national level, (%)	74	20
Antenatal care	Proportion of live births from women who have visited health professionals during pregnancy, National level, (%)	38	32

Table 4a. Estimation of Determinants of IMR : OLS
Dep Var=IMR

National Level		***Urban***		***Rural***	
Lgdp_intMA	-17.473	NA		NA	
	*(2.75)***				
asset_tot	0.708	asset_urb	-0.456	asset_rur	-0.728
	-1.5		*(2.27)**		*-1.41*
MAruralpop	-0.879	MAhexpshare	-1.379	MAhexpshare	-1.636
	*(3.40)***		*(2.18)**		*-1.24*
MAhexpshare	-3.082	Prim_UrF	-0.088	Prim_RuF	-0.332
	*(3.12)***		*-0.49*		*-1.37*
Prim_totF	0.144	Sec_UrF	-0.318	Sec_RuF	-0.078
	-0.66		*-1.52*		*-0.25*
Sec_totF	0.27	vacc_urb	0.073	vacc_rur	-0.203
	-1.01		*-0.59*		*-1.21*
Know about ORS	0.535	pipeWat_urb	-0.083	wellWat_rur	0.218
	*(3.13)***		*-0.45*		*-1.11*
Breastfed2_3	-0.123	flusToil_urb	-0.09	pitToil_rur	0.04
	-1		*-0.44*		*-0.33*
Vacc1year_tot	-0.387	pitToil_urb	-0.119	elec_rur	-0.321
	*(2.05)**		*-0.79*		*-1.71*
pipeWat_tot	-0.153	elec_urb	-0.332	Constant	126.788
	-0.65		*(2.16)**		*(6.30)***
surWat_tot	-0.166	Constant	131.582		
	-0.79		*(8.97)***		
flusToil_tot	-0.795				
	*(3.61)***				
pitToil_tot	-0.303				
	*(2.46)**				
elec_tot	-0.745				
	*(2.83)***				
Constant	288.114				
	*(6.41)***				
No. Obs	41		44		46
R^2	0.88		0.77		0.68

Note: 1. Robust t-statistics in italic or parentheses, * significant at 5% level; ** significant at 1% level;

2. F test for prim_urf sec_urf vacc_urb pipewat_urb flustoil_urb pittoil_urb, $F(6,33)=0.85$; F test for prim_ruf vacc_rur wellwat_rur pittoil_rur elec_rur, $F(5, 31) = 4.63$, significant at 1% level.

3. We repeat the above regressions replacing MAhexpshare by 3-year moving average of per capita health expenditure (PPP$). The results change very little, except that per capita expenditure is never statistically significant.

4. We also conducted sensitivity tests of the above results to outliers by deleting each country sequentially in the regression. The estimated coefficient of elec_tot appears sensitive to the exclusion of Mozambique (-1.07), with a range of -0.68 to -0.88; The results for urban data are relative robust, with the coefficient of elec_urb ranging from -0.28 to -0.42.

Table 4b. Estimation of Determinants of U5MR : OLS
Dep Var = U5MR

National level		***Urban***		***Rural***	
Lgdp_intMA	-37.333	NA		NA	
	*(2.93)***				
asset_tot	0.333	asset_urb	-0.755	asset_rur	-1.279
	-0.29		*-2.01*		*-0.86*
MAruralpop	-1.58	MAhexpshare	-1.31	MAhexpshare	-4.229
	*(3.44)***		*-1.06*		*(2.62)**
MAhexpshare	-4.192	Prim_UrF	-0.508	Prim_RuF	-0.616
	-1.98		*-1.3*		*-1.35*
Prim_totF	0.054	Sec_UrF	-0.47	Sec_RuF	0.283
	-0.15		*-1.37*		*-0.39*
Sec_totF	0.931	vacc_urb	0.043	vacc_rur	-0.739
	-1.66		*-0.25*		*(2.05)**
Know about ORS	0.422	pipeWat_urb	-0.267	pipeWat_rur	0.152
	-1.18		*-1.06*		*-0.2*
Breastfed2_3	-0.236	flusToil_urb	-0.449	wellWat_rur	0.849
	-1.19		*-1.12*		*-1.42*
Vacc1year_tot	-0.99	pitToil_urb	-0.47	pitToil_rur	0.026
	*(2.22)**		*-1.31*		*-0.13*
pipeWat_tot	-0.523	elec_urb	-1.023	elec_rur	-0.969
	-1.06		*(3.75)***		*-1.71*
surWat_tot	-0.875	Constant	295.983	Constant	224.309
	-1.52		*(9.25)***		*(5.56)***
flusToil_tot	-0.732				
	-1.44				
pitToil_tot	-0.535				
	-1.96				
elec_tot	-1.713				
	*(4.17)***				
Constant	643.503				
	*(5.53)***				
No. Obs	41		44		46
R2	0.89		0.85		0.8

Note: 1. Robust t-statistics in Italic or parentheses, * significant at 5% level; ** significant at 1% level;

2.F test for asset_urb MAhexp prim_urf sec_urf vacc_urb pipewat_urb flustoil_urb pittoil_urb, $F(8, 32) = 2.20$, significant at 10%; F test for asset_rur MAhexpshare prim_ruf vacc_rur wellwat_rur pittoil_rur elec_rur, $F(7, 30) = 5.81$, significant at 5%.

3. We repeat the above regression replacing MA health expenditure share by MA per capita health expenditure (PPP$). The results remain very close to above, except that per capita expenditure is never statistically significant.

4.The sensitivity tests show that results at the national level are relatively robust, with the coefficient of ele_tot ranging from -1.39 (dropping Senegal) to -1.92 (dropping Dominican Republic); Vacc1year_tot ranging -1.25 (Peru) to -0.73 (Zambia); coefficient of PitToil_tot ranging from -0.83 (Zambia) to -0.48 (Namibia). The estimated coefficient for elec_urb changes from -1.145 (dropping Namibia) to -0.86 (dropping Zambia). For the rural data, the coefficient of vacc-rur ranges from -0.86 (dropping Brazil) to -0.52 (dropping Nicaragua); and the coefficient of elec_rur ranges from -1.23 (dropping Jordan) to -0.48 (dropping Philippines).

Table 5. Verifying Electricity Effect: aggregate data
Dep V=U5MR

	mod-1	***mod-2***	***mod-3***	***mod-4***	***mod-5***	***mod-6***
elec_tot	-1.70	-1.60	-2.06	-1.77	-2.1	
	*(6.85)***	*(3.59)***	*(4.04)***	*(4.63)***	*(4.29)***	
Lgdp_intMA		-36.3		-38.4		-71.0
		*(2.42)**		*(3.08)***		*(5.36)***
asset_tot		1.2		1.0	0.0	
		-1.4		*1.0*	*0.0*	
All Other Vars			included	included	included	
No. Obs	41	41	41	41	41	41
R2	0.67	0.73	0.86	0.89	0.86	0.61

Note: Robust t-statistics in parentheses
* significant at 5% level; ** significant at 1% level

Table 6. Effectiveness Analysis for Selection of Interventions

		Avert 1 Infant Death (per 1000 Births)					
		Linear model			Nonlinear model		
		Total	*Urban*	*Rural*	*Total*	*Urban*	*Rural*
GDP-per capita (ppp$)	(%)	5.7			11.8 *(5.6; 48.6)*		
Health expenditure share		0.32	0.73		0.37 *(0.2; 1.5)*	0.63 *(0.3; 2.8)*	
Access to flush Toilets		1.26			0.97 *(0.5; 3.9)*		
Access to Pit toilet Latrine		3.30			4.56 *(2.1; 18.7)*		
Access to electricity		1.34	3.01		1.43 *(0.7; 5.8)*	4.08 *(1.8; 18.2)*	
Vaccination 1year of life		2.58			3.23 *(1.5; 13.3)*		

		Avert 1 Under 5 Child Death (per 1000 Births)					
		Linear model			Nonlinear model		
		Total	*Urban*	*Rural*	*Total*	*Urban*	*Rural*
GDP-per capita (ppp$)	(%)	2.7			6.0 *(2.2; 30.5)*		
health expenditure share		0.24			0.21 *(0.08; 1.09)*		
Access to flush Toilets		1.37			0.65 *(0.24; 3.35)*		
Access to Pit toilet Latrine		1.86			2.67 *(0.97; 13.7)*		
Access to electricity		0.58	0.98	1.10	0.63 *(0.23; 3.24)*	1.58 *(0.72; 4.45)*	0.69 *(0.26; 2.9)*
Vaccination 1year of life		1.01			1.66 *(0.6; 8.5)*		
Vaccination coverage				1.36			1.97 *(0.7; 8.5)*

Note: Below are countries with lowest or highest mortality rate.

	Infant Mortality Rate		
	National	*Urban*	*Rural*
Mean	84.6	62.9	84.6
Lowest	16.5	23.2	23.4
	Colombia1995	Vietnam1997	Colombia 1995
Highest	134.6	108.3	159.7
	Mozambique1997	Tanzania 1992	Mozambique 1997

	Under 5 Mortality Rate		
	National	*Urban*	Rural
Mean	123.0	101.8	142.3
Lowest	22.6	30.4	33.6
	Colombia 1995	Vietnam 1997	Colombia 1995
Highest	318.3	210.0	346.9
	Niger 1992	Niger 1992	Niger 1992

Note: 1. The units are per centage point, except for that specified. 2. If cost data for each investment or intervention are available, we can perform a cost-effectiveness analysis for selecting interventions by multiplying the cost data to the above numbers . 3.In the nonlinear model, we assume diminishing returns in mortality rates for each intervention, i.e. using semi-log specification. 4. The above numbers for the nonlinear model are calculated using the medium of IMR and U5MR from the sample, and numbers in brackets are two end estimates using minimum and maximum mortality rates from the sample.

Appendix Tables

Table 1. DHS Countries and Survey Years by Region

Sub-Saharan Africa		***Europe/Eurasia***	***Asia***	***Latin America & Caribbean***
Benin 1996	Mali 1987	Kazakhstan 1995	Bangladesh 1994	Bolivia 1994
Botswana 1988	Mali 1996	Kyrgyz Republic 1997	Bangladesh 1997	Bolivia 1998
Burkina Faso 1992	Morocco 1987	Turkey 1993	India 1993	Brazil 1986
Burkina Faso 1999	Morocco 1992	Turkey 1998	India 1999	Brazil 1991
Burundi 1987	Mozambique 1997	Uzbekistan 1996	Indonesia 1987	Brazil 1996
Cameroon 1991	*Namibia 1992*		Indonesia 1991	Colombia 1986
Cameroon 1998	Niger 1992		Indonesia 1994	Colombia 1990
CAR 1994	Niger 1998		Indonesia 1997	Colombia 1995
Chad 1997	Nigeria 1990		Nepal 1996	Dominican Republic 1986
Comoros 1996	Ondo State 1986		Pakistan 1991	Dominican Republic 1991
Cote d'Ivoire 1994	Rwanda 1992		Philippines 1993	Dominican Republic 1996
Egypt 1988	Senegal 1986		Philippines 1998	Ecuador 1987
Egypt 1992	Senegal 1993		Sri Lanka 1987	El Salvador 1985
Egypt 1995	Senegal 1997		Thailand 1987	Guatemala 1987
Eritrea 1995	Sudan 1990		Vietnam 1997	Guatemala 1995
Ghana 1988	Tanzania 1992		China 1992	Guatemala 1999
Ghana 1993	Tanzania 1996			Haiti 1994
Ghana 1998	Togo 1988			Mexico 1987
Guinea 1999	Togo 1998			Nicaragua 1997
Jordan 1990	Tunisia 1988			Paraguay 1990
Jordan 1997	Uganda 1988			Peru 1986
Kenya 1989	Uganda 1995			Peru 1992
Kenya 1993	Yemen 1991			Peru 1996
Kenya 1998	Yemen 1997			Trinidad & Tobago 1987
Liberia 1986	Zambia 1992			
Madagascar 1992	Zambia 1996			
Madagascar 1997	Zimbabwe 1988			
Malawi 1992	Zimbabwe 1994			

Table 2a. Correlation Coefficient Matrix: Aggregated data
(obs=41)

	IMRq0	CMR5q0	Lgdp_intMA	MAhexpshare	prim_totf	sec_totf	prim_totm	sec_totm
IMRq0	1							
CMR5q0	0.9351	1						
Lgdp_intMA	-0.7911	-0.7799	1					
MAhexpshare	-0.4333	-0.4353	0.3967	1				
prim_totf	-0.2003	-0.3099	0.1458	0.2492	1			
sec_totf	-0.6635	-0.6542	0.5392	0.299	-0.0846	1		
prim_totm	-0.0562	-0.183	0.0051	0.1197	0.9529	-0.2936	1	
sec_totm	-0.6066	-0.6044	0.4665	0.2657	-0.1305	0.9742	-0.3278	1
breastfed2_3	-0.0951	-0.1518	-0.0111	-0.1581	0.2484	-0.0463	0.2985	-0.0228
pipewat_tot	-0.7424	-0.7646	0.7973	0.4651	0.118	0.6671	-0.0334	0.578
wellwat_tot	0.6502	0.7403	-0.598	-0.2778	-0.432	-0.511	-0.322	-0.4354
flustoil_tot	-0.7346	-0.7165	0.8307	0.4123	0.1855	0.4921	0.0552	0.417
pittoil_tot	0.1	0.0276	-0.3796	-0.0822	0.1426	0.081	0.1686	0.1143
elec_tot	-0.8186	-0.8213	0.8	0.3643	-0.0119	0.82	-0.1855	0.7614
asset_tot	-0.7782	-0.7644	0.8227	0.3832	-0.0747	0.7711	-0.2373	0.6873

	breastfed2_3	pipewat_tot	wellwat_tot	flustoil_tot	pittoil_tot	elec_tot	asset_tot
breastfed2_3	1						
pipewat_tot	-0.0858	1					
wellwat_tot	-0.2215	-0.7666	1				
flustoil_tot	0.0751	0.8051	-0.5482	1			
pittoil_tot	-0.1161	-0.1312	-0.1037	-0.5238	1		
elec_tot	-0.0468	0.8528	-0.6275	0.7739	-0.1362	1	
asset_tot	-0.0475	0.8857	-0.5985	0.8364	-0.224	0.9378	1

Table 2b. Correlation Coefficient Matrix: Urban data

(obs=43)

	q01_urb	q05_urb	asset_urb	prim_urf	sec_urf	elec_urb	pipewat_urb	surwat_rur	flustoil_rur	pittoil_rur	vacc_urb	MAhexpsha
q01_urb	1											
q05_urb	0.9185	1										
asset_urb	-0.7592	-0.7845	1									
prim_urf	0.2538	0.1469	-0.4478	1								
sec_urf	-0.7026	-0.6848	0.6682	-0.4389	1							
elec_urb	**-0.8055**	**-0.8787**	**0.8245**	-0.2456	0.6642	1						
pipewat_urb	-0.5521	-0.6234	0.5268	-0.0486	0.5118	0.5632	1					
surwat_rur	0.207	0.1363	-0.3906	0.4712	-0.0276	-0.1033	-0.1243	1				
flustoil_rur	-0.5146	-0.5079	0.5146	0.0192	0.1987	0.46	0.2322	-0.2506	1			
pittoil_rur	-0.185	-0.2656	0.0481	0.0361	0.3365	0.1344	0.1719	0.0864	-0.2804	1		
vacc_urb	-0.0738	-0.1475	0.0009	0.2649	0.0278	0.0651	0.4888	0.0801	0.1757	-0.0029	1	
MAhexpshare	-0.4239	-0.417	0.3059	0.0737	0.2945	0.3184	0.4593	-0.0883	0.1264	0.0657	0.2414	1

Table 2c. Correlation Coefficient Matrix: Rural data

(obs=44)

	q01_rur	q05_rur	asset_rur	MAruralpo	MAhexps	vacc_rur	pittoil_rur	flustoil_rur	surwat_rur	pipewat_rur	elec_rur	sec_ruf	prim_ruf
q01_rur	1												
q05_rur	0.9321	1											
asset_rur	-0.6606	-0.6586	1										
MAruralpop	0.4316	0.5203	-0.4872	1									
MAhexpshare	-0.3805	-0.413	0.1984	-0.3444	1								
vacc_rur	-0.5408	-0.623	0.3387	-0.2723	0.4831	1							
pittoil_rur	-0.2959	-0.3524	0.2463	0.0534	0.1131	0.3644	1						
flustoil_rur	-0.5295	-0.4918	0.5018	-0.5667	0.1	0.3345	-0.2857	1					
surwat_rur	0.0933	-0.0026	-0.4217	0.0497	-0.0303	0.0966	0.1093	-0.2563	1				
pipewat_rur	-0.6755	-0.6956	0.764	-0.5597	0.1765	0.3663	0.3104	0.4719	-0.3238	1			
elec_rur	-0.667	-0.6834	0.9107	-0.4629	0.1202	0.2697	0.3021	0.4718	-0.3678	0.7827	1		
sec_ruf	-0.5474	-0.5436	0.7626	-0.1874	0.0971	0.3035	0.4745	0.1096	-0.1708	0.5693	0.8187	1	
prim_ruf	-0.4388	-0.5267	0.0399	-0.4143	0.4115	0.5604	0.1934	0.3517	0.4552	0.2492	0.071	-0.0064	1

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